Evaluation of Factors Affecting Inverse Beacon Fingerprinting Using Route Prediction Algorithm

Mathangi Sridharan, Paul Michael Campbell, Eliane Bodanese, and John Bigham

School of Electronic Engineering and Computer Science
Queen Mary University of London
London, United Kingdom
Email: m.sridharan@qmul.ac.uk, p.m.campbell@se16.qmul.ac.uk, eliane.bodanese@qmul.ac.uk, john.bigham@qmul.ac.uk

***Abstract*— Conventional Radio Frequency (RF) based fingerprinting still remains one of the most popular methods amongst other indoor positioning techniques due to its inherent accuracy and reliability. However, not much prominence has been shown in analyzing certain factors that may affect the outcome of the fingerprinting method while designing the localization system. In this paper, we conduct a study to infer if a reduced number of receivers equipped with higher gain antennas can provide improved Bluetooth Low Energy (BLE) fingerprinting performance in a complex indoor environment. The evaluation is performed in a standard domestic apartment with an activity centric approach using a single wearable beacon and multiple receivers. A rank based route selection algorithm is used to list the candidate positions or routes that indicate the most likely path on which the subject was travelling. Furthermore, we discuss the benefits of implementing the inverse fingerprinting method with a trajectory based prediction model and also examine the effect of surrounding electrical interference. Experimental results indicate that an increased antenna gain in addition to deploying an adequate number of receivers have a positive effect on the overall ranking accuracy.**

Keywords*— *RSSI Fingerprinting; beacon; indoor localization; receiver antenna gain; Bluetooth Low Energy; activity recognition

I. INTRODUCTION

Radio Frequency (RF) fingerprinting techniques using different wireless technologies are often considered to be suitable for indoor localization since they provide better performance when compared to triangulation [1-2]. Received Signal Strength Indicator (RSSI) fingerprinting involves two important stages; the offline training phase and the online positioning phase. In order to build a radio map during the offline training phase, a detailed site survey is performed where sufficient number of RSSI samples are collected at known locations. During the online positioning phase, the gathered RSSI samples from one or more receivers are compared against the radio map using deterministic or probabilistic methods to estimate the target's location. One of the limitations associated with fingerprint based systems is the labor-intensive construction of the radio map. However, methods with reduced workload have been introduced recently such as implementation of crowd sourcing techniques to train the system automatically [3-4] or incorporating robots to do the survey process [5-6].

Fingerprinting using Wi-Fi has been quite popular and well established as it can make use of the existing infrastructure containing access points (AP). But ever since the introduction of iBeacon protocol based on Bluetooth Low Energy (BLE) technology; the low cost, power efficient beacon has carved a niche for itself in indoor localization research and in the commercial market. Performance analysis done by Zhao et al. on BLE and Wi-FI in the same test environment indicates that the former outperformed the latter by around 27 percent [7]. BLE beacons are therefore used in this study owing to its several advantages over Wi-Fi.

Despite the recent advances in indoor positioning systems, setting up a reliable smart space for localization in compact domestic homes still remains an open challenge. One of the reasons of not being able to devise a practical localization solution for small-scale homes is mainly due to the dynamic nature of a domestic space that is constantly subjected to heavy attenuation caused by the surrounding walls and furniture. Deploying independent RF fingerprint based solutions in such compact spaces will prove ineffective, as the signal will be unstable in a strong non-line of sight (NLOS) environment. To develop a potential RF fingerprinting system for a home environment, importance has to be extended in choosing the right hardware elements and data collection method, apart from improving the location estimation algorithm.

Motivated by the above, this paper will provide an insight into the concept of ranking accuracy, which is used as the metric for performance analysis of the BLE fingerprinting method. Furthermore, we discuss in-depth the impact of control variables such as receiver antenna gain, route length, number of detected receivers on the ranking accuracy of routes followed by a brief overview on the effect of surrounding electrical interference on the beacon signal. The results from this study can help improve the BLE fingerprinting performance and can also be used along with other technologies such as magnetic field positioning and pedestrian dead reckoning (PDR) to bring about improved localization in small-scale homes [8]. This opens up the door for installation

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of a variety of monitoring applications for sheltered accomodation, which are typically studio or one-bedroom apartments. Location estimation algorithms are not the focus of this paper as there is sufficient research already carried out on them. The key findings from this study will help the reader consider different factors that can help improve the overall performance of the RF localization system, and will serve as a reference case study for future research when deciding on hardware characteristics during deployment of RF fingerprint based indoor positioning systems.

The rest of the paper is organized as follows; we discuss related work in Section II. Section III provides an overview on the design and implementation of the experimental setup followed by a brief explanation of the route prediction algorithm. The performance analysis results of various factors including antenna gain and electrical interference are discussed in Section IV. Section V concludes the paper.

II. Related Work

Some of the important factors that determine the accuracy of this type of scene survey method is the procedure used for collecting RSSI fingerprints, the accuracy of the radio map, the location estimation algorithm and other miscellaneous factors, such as hardware setup and configuration, building layout and environment noise. Apart from the location estimation algorithm and the data collection procedure, there has been minimal research done in evaluating other factors that affect indoor location fingerprinting systems. It is essential to take note of these external elements while designing a stable location aware system. One such quality control study by Liu et al. involves analyzing and summarizing the potential impact factors affecting Wi-Fi fingerprinting that is implemented on a simulation platform [9]. The research involves studying various factors such as AP density, AP distribution, radio signal attenuation factor, radio signal noise, and reference point (RP) density. The final results indicate that an increase in AP density, RP density and the signal attenuation factor with low signal noise level contribute to better performance. The study also claimed that the AP distribution had no particular impact on the end result. In another study conducted by Moghtadaiee et al., the design characteristics such as the effects of the number and geometry of APs, RPs and number of RSSI samples for an indoor positioning system were analyzed [10]. Results from this study revealed that merely increasing the number of APs beyond a suitable number for a given indoor space barely influences the end result. The attenuation caused by the human body is another key factor to be considered in indoor positioning systems. At most times, accuracy is affected when a human body shields the direct line of sight path between the transmitter and the receiver. A number of studies have introduced compensation factors into the positioning algorithm to account for the path loss encountered due to the presence of a human body [11-12]. In [13], the fluctuations in signal strength in indoor environment caused by human movement are studied. Various attenuation models based on movement speed were built for a single-person and three-person scenario. Though the effect of the human body was not studied in detail in the research presented in this paper, readings were collected in all directions for a given path to ensure that the interference from signals passing through the human body was taken into account while creating the radio map.

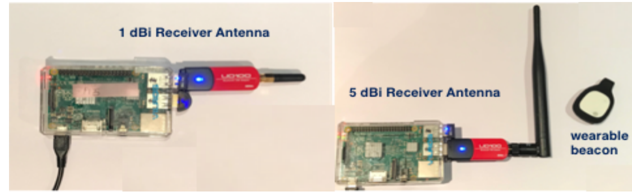

Fig. 1. Project hardware components: Raspberry-Pi receivers with external 1dBi and 5dBi antennas along with wearable beacon

III. Design And Implementation Of The Experimental Setup

A. Inverse Beacon Fingerprinting

Efforts have been undertaken in the past to develop a competent system for varied applications that employ multiple beacons at fixed positions and use a smartphone or any moving beacon signal receiver for indoor positioning. This type of design takes a toll on the battery life of the receiver where most of the processing and computations are done [14]. Moreover, using a smart phone for location estimation is impractical for health related monitoring applications such as elderly monitoring or monitoring of patients suffering from Alzhiemer's disease or depression at home as the person is not expected to carry the phone at all times. Hence, there is a necessity to design a non-intrusive positioning system that can provide useful information to other health monitoring or activity recognition systems at home. In our setup, we have used a wearable beacon and placed multiple receivers at fixed points to determine the location of the resident. This approach is referred to as the "*inverse beacon positioning*" method since the beacon is in motion as opposed to the conventional method of placing it in a fixed position. A similar setup was followed in [14], where the positioning computations were performed by multiple fixed sniffers implemented on Raspberry-Pis and a cloud based central server, while the testing was done using a smart phone carried by the user. The benefits of this type of implementation include power efficiency of the user device making it suitable for long-term tracking services. Furthermore, the use of a wearable eliminates the issue of device diversity encountered by using different models of smart phones and is also a better choice for developing monitoring applications at home.

B. Hardware Considerations

Raspberry-Pi 3 Model B devices were used as receivers of the RSSI signal from the broadcasting beacon in this study. The setup and testing was done in a one-bedroom apartment (10.57m x 4.44m), where five Raspberry-Pis were deployed in different rooms such that coverage is provided for the entirety of the property, and the placement of the receivers were chosen as per the activities to be monitored. The wearable used in this study is a MetaMotionR beacon with embedded sensors manufactured by MbientLab [15]. This device is also capable of measuring magnetic field strength, acceleration and step count, and comes enclosed in a waterproof casing with a rubber clip on. To avoid the possibility of differing performance characteristics between different Bluetooth chips, each Raspberry-Pi was equipped with a Sena UD100-G03 Bluetooth

The author sequence stated in this paper follows the "sequence-determines-credit" (SDC) approach.

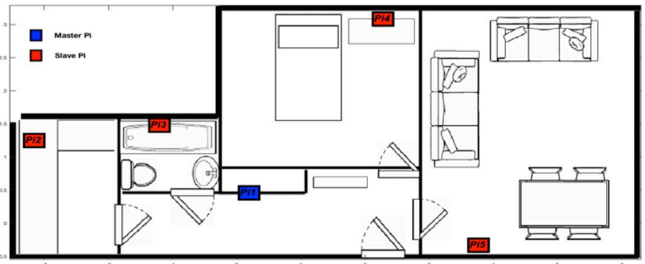

Fig. 2. Property layout and Raspberry-Pi locations

USB dongle that supported interchangeable antennas (Refer to Fig.1). External omnidirectional antennas (1dBi and 5dBi) were chosen for the evaluation on antenna gain and therefore, the on-board Bluetooth module in the Raspberry-Pi receivers were disabled.

C. *Training Stage Data Collection Process and Implementation*

A number of walking routes were selected to reflect regular domestic human behavior to provide the most realistic scenario for testing. The entirety of the property was chosen to be used for the investigation. We opted for a trajectory based sequential method of data collection rather than the conventional method of using the global coordinate system for location mapping as this approach is much less strenuous and more suitable for mapping contextual information to an activity recognition framework. Moreover, prior research suggests that position estimation using sequential RSSI values along a path is more resilient to changes in the surrounding environment as they have a distinct signature [4,8,16].

During the training phase, the RSSI samples were collected at specific points along each walking route with a length between each step measuring approximately 0.5m. Each of these measures were collected over a period of 60 seconds in all directions applicable for a given route. This process was carried out for both the 1 dBi and 5 dBi antennas – a total of 176 readings. The beacon broadcasting frequency was set to 100ms and the final radio map consisted of radio signal readings collected at intervals of one second. A master-slave approach was used to collect and combine the beacon RSSI data from all the Raspberry-Pi receivers. The RSSI collection and data transfer process between the receivers is explained in detail in our previous published work [8]. The layout of the trial home along with the placement of the master and slave Raspberry-Pi receivers is illustrated in Fig. 2.

D. *Route Prediction Rank Based Algorithm*

For determining the correct path during the online phase, a section of routes were tested by physically walking along the trajectory and collecting RSSI data whilst moving. The collected RSSI data was then passed to a prediction algorithm that outputs a list of routes ranked in order of descending likelihood to the actual route walked by the resident. The first step involved sorting the entire training database and the collected online beacon signal samples based on their strongest RSSI vectors. RSSI values with "-120" collected by receivers are indexed as zero referring to the fact that the respective Raspberry-Pis is out of range of the beacon. This is followed by creating a rank matrix individually for the offline and online

Algorithm 1 Route Prediction Using RSSI Fingerprinting

Inputs: $\boldsymbol{RSS_{offline}}$ = Offline radio map with labeled routes, $\boldsymbol{RSS_{online}}$ = Online RSSI data, $\boldsymbol{n}$ = number of receivers considered, $\boldsymbol{RPi_{ID}}$ = Raspberry-Pi Identifier *where* (1≤ ID ≤ n)
Output: ***selectedRoutes*** = Top 10 most likely routes ranked in decreasing order of likelihood that was walked by the target.

for i = 1: *sizeof* ($\boldsymbol{RSS_{offline}}$) **do**
  Compute rank matrix '**α**' where each row 'i' contains the $\boldsymbol{RPi_{ID}}$ sorted in descending order based on the strongest RSSI
end for
for i = 1: *sizeof* ($\boldsymbol{RSS_{online}}$) **do**
  $\boldsymbol{I_{online}}$ ← Sort $\boldsymbol{RPi_{ID}}$ in descending order based on the strongest incoming $\boldsymbol{RSS_{online}}$
  β[i] ← Retrieve respective walking route label of matched rows in $\boldsymbol{I_{online}}$ from '**α**'
  occ**[i]** ← Compute the frequency of occurrence of matched walking routes in **β[i]**
end for
γ ← Results from '**β**', categorized by ***group_occ*** = number of routes grouped by ***occ*** and ***sum_occ*** = total number of observations of each route.
δ ← Sort Routes in '**γ**' based on ***sum_occ*** and on ***group_occ*** incase of ties.
return *selectedRoutes* ← Retrieve top 10 walking routes from **'δ'**

data where each row contains the corresponding Raspberry Pi identifier based on the previous sorting. The ranked datasets are finally matched against each other to find the top ten most likely routes that was walked by the target person. The Pseudo code explaining the above steps is shown in Algorithm 1.

E. *Advantages and Applications*

This analysis is an extension of the research done in [8]. A two-step fingerprinting operation was carried out in [8], where the results of the beacon fingerprinting technique was used to narrow down the search area for the fingerprinting method using magnetic signatures. This hybrid approach ensured a reasonable localization performance in compact homes. In this paper, we perform a deeper analysis of the factors that help in raising the accuracy of the beacon fingerprinting method, such that the probability of the actual route appearing in the top ten or top five positions using Algorithm 1 are improved. This approach is tested in a one bed apartment and would be useful in designing a reliable Activities of Daily Life (ADL) monitoring system or can be developed into a suitable user-friendly Internet of Things (IoT) application. The proposed technique can also be extended to an industrial environment where location based services play a pivotal role in supply chain management or can help managers to collect and analyze information regarding the worker's movement patterns. This paper serves as a reference case study for solutions that use RSSI fingerprinting as one of the techniques for indoor positioning in an industrial or domestic environment. The experiments conducted in this study provides an insight on how the efficacy can be improved using the deployed hardware.

IV. Results And Analysis

The training database comprised a total of 36 routes including stationary points. RSSI data samples for the 24 walking routes listed in Table I were selected to study the performance analysis between receivers equipped with 1dBi and 5dBi antennas individually, out of which 17 routes were measured 4 times (Route No. 1 to 20) and 7 routes were

TABLE I. LIST OF WALKING ROUTES USED FOR THE ANALYSIS

Route No.	Route Name	Points on Route	Route Length (m)
1	Bathroom to kitchen fridge	6	2.7
2	Bedroom door to couch	8	5.7
3	Bedroom door to kitchen fridge	12	7
4	Bedroom door to front door	4	2
5	Couch to dining table	5	2.2
6	Couch to bedroom door	8	5.7
7	Couch to fridge	16	9.4
8	Couch to front door	8	4.4
9	Dining table to cooker	20	8.3
10	Dining table to couch	5	2.2
11	Fridge to bathroom	13	2.7
12	Kitchen fridge to bedroom door	12	7
13	Sink to fridge	2	0.6
14	Bedroom to bathroom	10	6
15	Bed to wardrobe	10	4.6
16	Front door to fridge	8	5.6
17	Front door to toilet	8	4.6
18	Fridge to couch	16	9.4
19	Fridge to sink	2	0.6
20	Kitchen cooker to dining table	16	8.3
21	Front door to bedroom door	4	2
22	Bathroom to bedroom	10	6
23	Front door to couch 2	9	5.2
24	Couch 2 to front door	10	5.2

measured 10 times (Route No. 21 to 24). When a route was not found in the top ten rankings, it was assigned the value "eleven". In this section, the rank based route selection method explained in Algorithm 1 was used as the basis to assess the performance against various factors.

A. Impact of Antenna Gain on Ranking Accuracy of Routes

An evaluation was performed to assess if increased antenna gain improves the position of the correct route in the rankings using the method described in Section III. An analysis on the collective measurements of all walking routes yielded an average median rank of 7.58 for 1dBi antenna setup that improved to 6.1 when 5dBi antennas were deployed. Fig. 3 represents the corresponding individual average median route rankings for 1dBi and 5dBi antenna gain. The median was chosen to perform the analysis rather than the mean in order to reduce the effect of outliers. The average improvement in rank while using 5dBi antenna is a movement of 1.5 positions over 1dBi.

Since the same set of routes were walked for 1dBi and 5dBi setup, a Paired-t test was used to match the individual route rankings against each other to check if there is a significant difference in the results between these two groups. The difference is considered to be statistically significant if the p-value ≤ 0.05. In this case, the p-value was found to be 0.0324, which indicates a notable difference between the 1dBi and 5dBi measures. When the improvement of each route was analyzed individually, the rank of 67% of the walking routes improved while using 5 dBi antennas as opposed to their rank using the 1dBi stub antennas. Taking into account those that did not change, 91% of routes were equal or better at 5 dBi compared to 1 dBi gain.

It has to be noted that the sole use of this method will not help in accurate location positioning. The very purpose of this analysis was to check if an increased antenna gain helped in boosting the probability of a route appearing in the top 10 or top 5 positions consistently, so that the outcome of the method described in [8] is improved.

B. Correlation between Route Length and Rank Improvement

It was expected that there would be a direct correlation between the length of a specific route and an improved ranking. This was based upon the assumption that if the signature of the route was longer, it would more likely be unique and therefore, more accurately matched against the radio map built during the training stage. However, this was

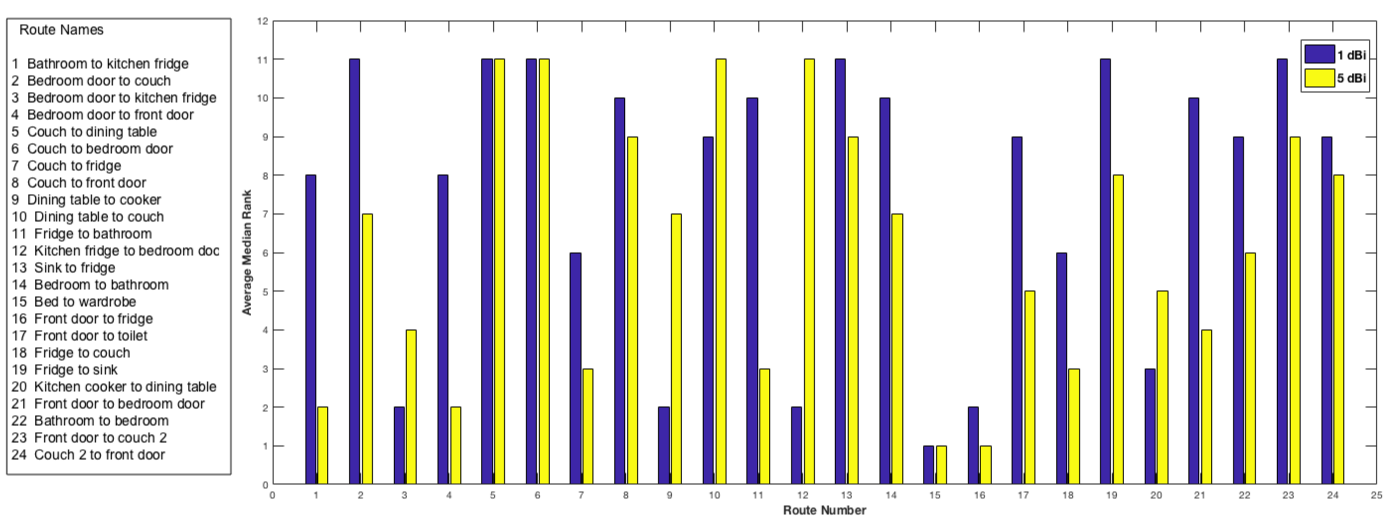

Fig. 3. Comparative average median rank analysis of 24 selected routes using 1dBi and 5dBi receiver antenna

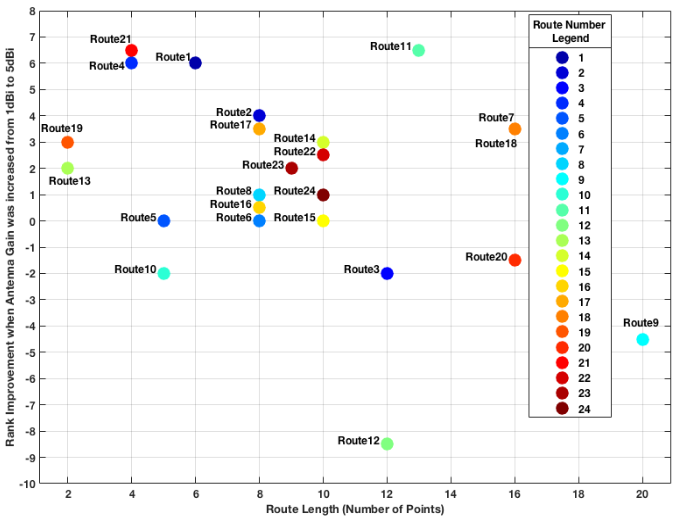

Fig. 4. Relationship between Route Length and Rank Improvement

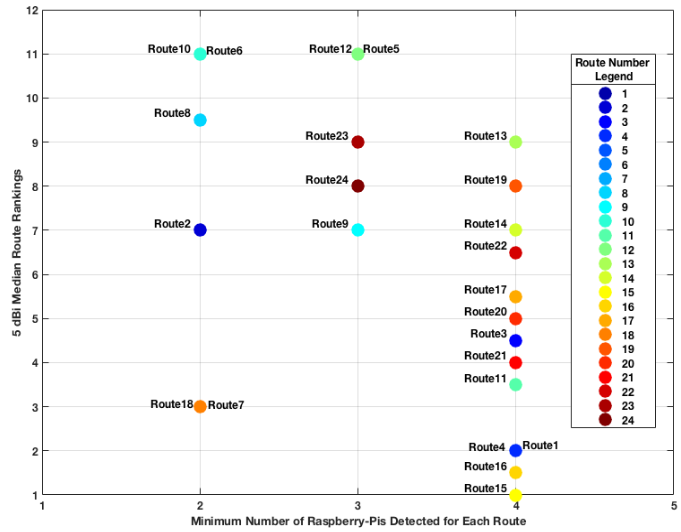

Fig. 5. 5dBi Median Route Rankings Vs Minimum Number of Raspberry-Pis detecting the beacon

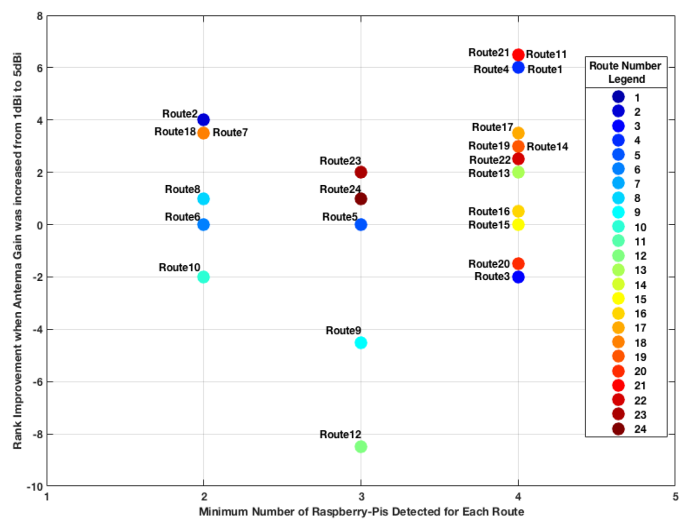

Fig. 6. Improvement in Rank Vs Minimum Number of Raspberry-Pis detecting the beacon

not the case as shown in Fig. 4.

A large percentage of the longer routes, which consist of more than 10 points, did not show a marked improvement in ranking when 5dBi antennas were used. In the graph of Fig. 4, a positive value of rank improvement is denoted as an increase in the rank position using 5dBi over 1dBi antennas. Likewise, a negative value indicates a decrease in the rank position. This may be due to the fact that longer routes cover numerous segments of existing shorter routes, making it harder to identify the exact walking route. The results highlight the fact that the most consistently improved routes in ranking are those between eight and ten points; primarily routes of medium length.

C. *Effect of the Number of detected Raspberry-Pis on the Ranking Accuracy*

1) 5dBi Median Route Rankings Vs Minimum Number of Raspberry-Pis detecting the beacon: Whilst there was no improvement in ranking performance due to the increased route length, it was noticed that the number of Raspberry-Pis detecting the beacon had a positive influence on the performance rankings for each route. For any given route, the number of Raspberry-Pis detecting the beacon can vary between one and five in this case study. In order to measure the performance efficiency, the minimum number of Raspberry-Pi receivers detecting the beacon was identified for each route along with their respective rank position outcome. The tests indicate that an increase in the minimum number of detected Raspberry-Pis raises the likelihood of improvement, which is reflected in the ranking position for a given route (as shown in Fig. 5).

In Fig. 5 plot, the y-axis identifies the rank, with one being the highest; all routes outside the top ten are demarcated by the value ‘eleven’. It is evident from this plot that a large section of routes (Route No. 1,3,4,11,13-17,19-22) have at least four Raspberry-Pis detecting the beacon as a result of using 5 dBi antennas at any given time. Around nine of these thirteen routes are found to have an average median rank ranging from one to five, confirming that the relative rankings improve with the increase in the number of receivers detecting the beacon.

2) Improvement in Rank Vs Number of Raspberry-Pis detecting the beacon: It was observed that the number of Raspberry-Pis detecting the beacon using 5dBi antennas were comparatively higher than when using 1dBi antennas (Refer Table II). Consequently, there was also an improvement in the average median rank by using receivers with higher antenna gain when the minimum number of Raspberry-Pis detecting the beacon increased (Refer to Fig. 6).

For instance, it was noted that the same routes (Routes: 1,3,4,11,13-17,19-22), which had at least four Raspberry-Pis detecting the beacon, were seen to improve in rank position or remain unchanged when the antenna gain was increased by 4 dBi. None of the routes were found to deteriorate in the rankings when the minimum number of receivers detected were four, and the performance worsened for only one route (Route No: 12 - Kitchen fridge to Bedroom door) when the number of receivers detected were three.

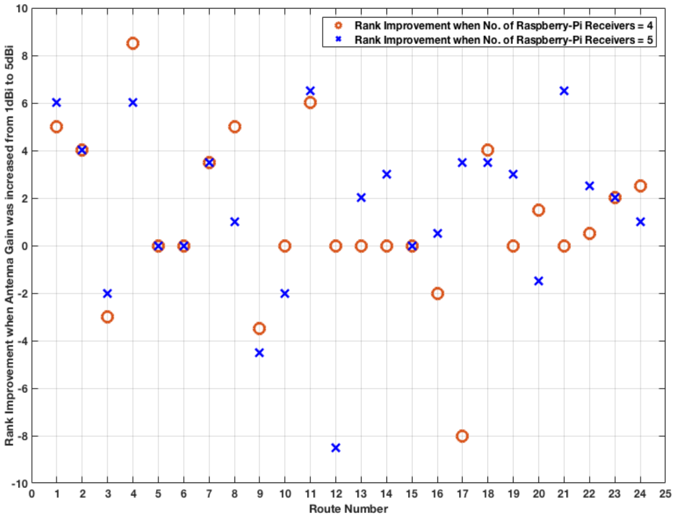

Fig. 7. Difference in rank improvement between Differing Number of Receivers

D. *Impact of Increased Antenna Gain on the Number of Raspberry-Pis Deployed*

Using the hypothesis that higher antenna gain increases the density of coverage within the property, it was considered a possibility that it would help reduce the number of Raspberry-Pis deployed in the test environment while maintaining sufficient accuracy. This was tested by removing the Raspberry-Pi located in the bathroom (Pi-3), because of its proximity to the Raspberry-Pi in the kitchen (Pi-2) and the one in the hallway (Pi-1) (Refer to Fig. 2). By line of sight measurement, the distances from the bathroom Raspberry-Pi to the hallway and kitchen Raspberry-Pi were 1.8m and 2.5m respectively. The resulting rankings were recomputed after removing Pi-3 from the training and test datasets.

To determine whether reducing the number of Raspberry-Pis to four had a detrimental impact on the route rankings, the average median rank improvement was investigated when the antenna gain was increased to 5dBi from 1dBi. It was observed that the average improvement in rank in the case of deploying four Raspberry-Pis was 1, compared to 1.5 with five Raspberry-Pi receivers (Refer to Fig. 7). In addition to the decreased average rank improvement, there was a significant reduction in the number of individual routes that improved in its ranking position while using four Raspberry-Pi receivers. It was found that only 45% of routes improved when four Raspberry-Pi receivers were used. The use of an additional Raspberry-Pi therefore presents a significant improvement in the overall performance. This would therefore suggest that there is a requirement for a receiver to be placed inside every room, when the beacon cannot be detected by all the Raspberry-Pis in the test property as matching against the fingerprint database will be less precise.

E. *Effect of Electrical Interference on Beacon Signal Measurement*

It was observed that the beacon RSSI readings were spurious at certain times of the day and inconsistent with the readings obtained at other times inside the apartment. It was presumed that this may be related to RF interference from another device in the testing area. To test this proposition, the MetaMotionR wearable was left at a particular location in the apartment for a long time period. A deeper inspection revealed that significant interference was observed when the washing machine started functioning. This phenomenon was verified through several tests confirming the result. Fig. 8 shows the placement of the washing machine denoted by ‘W’ and the beacon denoted by ‘B’ in the test apartment.

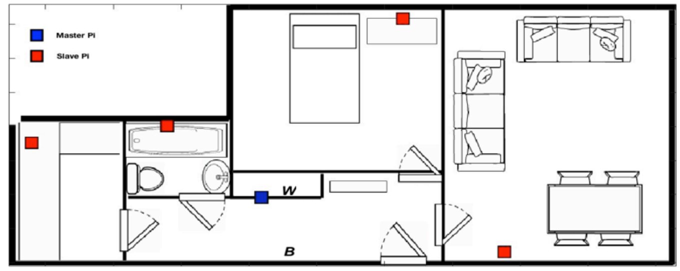

Fig. 8. Interference with respect to beacon position (B) and washing machine (W)

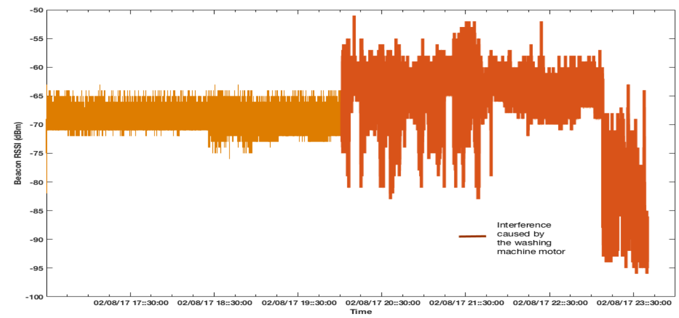

Fig. 9. Interference from a washing machine in the test apartment

The resulting RSSI signal variability due to interference was plotted against time as seen in Fig. 9. The washing machine was left on a timer and the rapid variability of the beacon signal can be clearly seen when the machine was in the middle of its operating cycle (right hand side of the chart). The effect of electrical interference should especially be kept in mind while collecting RSSI samples during the training stage as the entire positioning system depends on the accuracy of the radio map. This is a good example of the susceptibility of indoor localization systems using only RSSI data and should therefore be combined with other techniques mentioned in the earlier section to reduce the impact of electrical interference.

F. *Comparison of Using Onboard BLE Chip Against External BLE Antennas*

The Raspberry Pi 3 Model B has a built in Bluetooth radio with a maximum gain of 1.5 dBi. A brief comparison was made between the performance of the onboard chip and the external 1dBi and 5dBi dongles on the premise that a higher antenna gain increases the number of Raspberry-Pis that can detect the beacon. This behavior was confirmed earlier. Working on the principle that a higher number of receivers detecting the beacon improves the overall rank, a similar process of finding the minimum number of Raspberry-Pis detecting the beacon for all routes was estimated using the onboard BLE module. The number of Raspberry-Pis detecting the beacon for each walking route using 1dBi, 1.5dBi and 5dBi antennas is illustrated in Fig. 10 and the results summary for all the routes using these antennas are shown in Table II. The

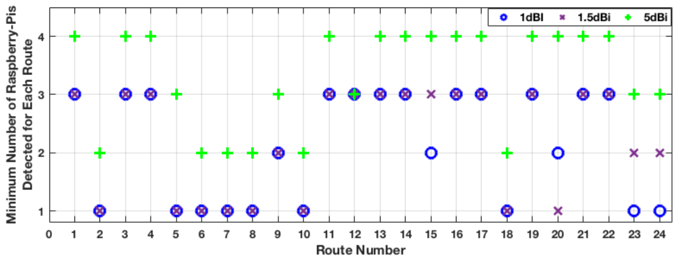

Fig. 10. Minimum number of Raspberry-Pis detected per route using 1dBi, 1.5dBi and 5dBi antennas

TABLE II. SUMMARY OF BEACON RANGE

Number of Raspberry-Pis detecting beacon	Number of Routes		
	1 dBi	*1.5 dBi*	*5 dBi*
4	0	0	13
3	12	13	7
2	3	3	6
1	11	10	0

results indicate that an increase in antenna gain of 0.5 dBi has little or no impact on the number of Raspberry-Pis that detect the beacon, and therefore, there will be no realistic improvement in the rankings. A more substantial increase in receiver antenna gain is therefore required to increase the number of Raspberry-Pis that are able to detect the beacon, as demonstrated by the marked improvement in performance while using the 5 dBi antennas.

V. CONCLUSION AND FUTURE WORK

There are very few indoor positioning systems specially designed to cater to a domestic environment. In this paper, we have designed and implemented a modified inverse procedure of RF fingerprinting using a beacon that uses a trajectory-based radio map model for location estimation. The main focus was on analyzing some of the hardware and external factors that influence the positioning performance of the beacon fingerprinting method. A direct comparison was made for a selected number of paths by using different interchangeable receiver antennas to assess the impact of antenna gain on the position of the correct route in the resulting rankings. It was found that an increase in antenna gain improves the range of the Raspberry-Pi receivers such that they can detect the beacon from a further distance. Consequently, it was proved that the performance of the fingerprinting system improved with the increase in the number of receivers detecting the beacon, and not with the increase in route length. Experimental results also suggest that the number of receivers deployed in the test environment have a strong influence on the localization performance. This was confirmed by removing a single Raspberry-Pi from the system and even with an increased antenna gain, the performance of the fingerprinting technique was found to deteriorate. Furthermore, it was observed that the electrical interference resulting from the washing machine motor had an undesirable effect on the beacon signal.

The study was carried out as part of our ongoing research project in developing an activity recognition system for clinically depressed patients at home. The analysis done in this paper will help in planning the setup and choosing the number of equipment required for a given area. Integrating localization and ambient sensor systems provide a significant boost to activity recognition results and can help bring down the deployment cost by using minimal sensor equipment. Future work will deal with enhancing the accuracy of the existing technique through the use of step counter data, which can help narrow down the candidates in the training database. Another important research topic is the optimal placement and orientation of the receivers and the impact of certain building properties such as wall thickness on the localization accuracy.

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